ASSESSING MULTI-DIMENSIONAL PERFORMANCE:

ENVIRONMENTAL AND ECONOMIC OUTCOMES

by

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Abstract

This study examines the determinants of environmental and economic performance for plants in three traditional smoke-stack industries: pulp and paper, oil, and steel. We combine data from Census Bureau and EPA databases and Compustat on the economic performance, regulatory activity and environmental performance on air and water pollution emissions and toxic releases. We find that plants with higher labor productivity tend to have lower emissions. Regulatory enforcement actions (but not inspections) are associated with lower emissions, and state-level political support for environmental issues is associated with lower water pollution and toxic releases. There is little evidence that plants owned by larger firms perform better, nor do older plants perform worse.

Key Words: Environmental Performance, Labor Productivity, Emissions, Enforcement Activity, Technology

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1. Introduction

During the past 30 years there have been substantial improvements in U.S. air and water quality due in large part to increasing stringency of regulation which has caused continuous declines in emissions from industrial sources. This study examines the determinants of both environmental and economic performance for plants in three traditional smoke-stack industries – pulp and paper, oil, and steel. We measure environmental performance by a plant's air, water, and toxic emissions per unit of output and economic performance by its labor productivity.

Much of the empirical research on the impact of environmental regulation has concentrated on the impact of reported pollution abatement costs on productivity.[1] However, there have been a few studies which examine the environmental performance of polluting plants including Magat and Viscusi (1990), Gray and Deily (1996), Laplante and Rilstone (1996), Nadeau (1997), Gray and Shadbegian (2005) and Shadbegian and Gray (2005). These studies have primarily focused on the efficacy of EPA enforcement in terms of raising compliance rates or lowering emissions. For example, three of the studies mentioned above show that plants which receive more air enforcement activity by regulators have better environmental performance in various ways: Gray and Deily (1996) find increases in compliance rates at steel mills; Nadeau (1997) finds decreases in the length of spells of non-compliance at pulp and paper mills; and Gray and Shadbegian (2005) find increases in compliance rates at pulp and paper mills. Furthermore, Magat and Viscusi (1990) find that water pollution enforcement activity reduces both water discharges and the probability of noncompliance at U.S. pulp and paper mills. Laplante and Rilstone (1996) examine the environmental performance of Canadian pulp and

[1] See Denison (1979), Gollop and Roberts (1983), Gray (1986,1987), Fare et al.(1989), Boyd and McClelland (1999), Berman and Bui (2001), and Gray and Shadbegian (2002,2003a).

paper mills and find that both actual inspections and the threat of an inspection reduce water discharges.

Shadbegian and Gray (2003) differ from the above studies by focusing on how differences across plants in air pollution abatement expenditures, local regulatory stringency, and productive efficiency impact environmental performance of pulp and paper mills. Using a cross-section of 68 pulp and paper mills they find that emissions are significantly lower at plants: with a larger air pollution abatement capital stock, which face more stringent local regulation, and with higher productive efficiency. Shadbegian and Gray also analyze the relationship between environmental performance and productivity using a seemingly unrelated regression model of air emissions and total factor productivity. In particular, they find a negative correlation between the residuals from those models, again indicating that plants which are more efficient in production are also more efficient in pollution abatement.

Our current study extends the work of Shadbegian and Gray (2003) in several significant ways. First, in addition to examining how EPA enforcement activity, local regulatory activity, pollution abatement spending, and productive efficiency impact environmental and economic performance for plants in the pulp and paper industry, we also examine how these factors impact performance of oil refineries and steel mills. Second, Shadbegian and Gray focus exclusively on the determinants of air emissions, while we also investigate the determinants of water emissions and toxic releases. Third, the timeframe for our study is 1990-2000, while the earlier work examined the 1980's. These extensions to the work of Shadbegian and Gray allow us to determine how consistent their results are across time and industries. Furthermore, we can examine whether or not there are any systematic relationships between our environmental outcome measures for air and water emissions as well as toxic releases. There are two rival explanations for the likely correlations across these different environmental performance measures. If plants differ in the quality of their environmental managers, those performing well on air pollution abatement might also do well on water pollution abatement. On the other hand, we might observe a negative correlation between air pollution abatement and toxic releases if the process of filtering particles from air emissions generates toxic sludge that requires disposal.

We use confidential annual plant-level Census data for 327 pulp and paper mills, 121 oil refineries, and 83 steel mills. From various Census data sources we can identify each plant's production, employment, capital stock, labor productivity, and age, along with its pollution abatement spending. To the Census data we add data from several EPA datasets on plant-level emissions of air, water, and toxic pollutants and enforcement activity. We also add characteristics of the plant's production technology taken from industry directories and firm financial data from Compustat.

Analyzing the results is complicated by our estimating 18 different equations (3 industries * 5 pollutants + productivity); hence we focus on patterns of coefficient signs and significance across equations rather than individual coefficients. We find that plants with higher labor productivity tend to have lower emissions. We also use Seemingly Unrelated Regressions (SUR) models, finding a positive correlation between a plant's residual performance on productivity and environmental performance measures, along with a positive correlation among the different environmental performance measures.

We test for the impact of regulatory activity using several measures, with mixed results. Plants facing more enforcement actions have lower emissions (as expected), but the reverse is true of inspections. Plants in states with greater political support for regulation have lower emissions of pollutants with more localized health effects (water and toxic, but not air).

Pollution abatement operating costs are positively related to emissions, surprising but similar to Shadbegian and Gray (2003). Finally, there is little evidence that newer plants, larger plants, or larger firms have better environmental performance.

Section 2 provides some information about the generation of air and water pollution in the paper, oil, and steel industries. Section 3 presents a brief model of the determinants of environmental and economic performance. Section 4 describes the data used in the analysis. In section 5 we describe the major econometric issue with our analysis – endogeneity of environmental regulation. Section 6 provides the results, and section 7 concludes the paper.

2. Air and Water Pollution in the Paper, Oil and Steel Industries

The three industries we study in this paper – paper, oil and steel – are all heavy emitters of both air and water pollution. For example, in 1996 each of these industries ranks in the top six of all 2-digit SIC in terms of fine particulate and sulfur dioxide (SO_2) emissions per dollar of output (see Aiken and Pasurka (2003)). These three industries are also among the top users of industrial process water and thus have major water pollution concerns as well. Now we describe in a little more detail the pollution concerns of each of our three industries.

Pulp and paper mills are a major emitter of both air pollution – particulates ($PM_{2.5}$), SO_2, and nitrogen oxides (NOX) – and water pollution – biological oxygen demand (BOD) and suspended solids (TSS). The majority of air pollution is created during the pulping stage of paper production. Pulp mills and integrated mills (paper mills that incorporate a pulping process) have large boilers which burn fossil fuels, liquor waste solids, and wood wastes to generate power, thus creating the potential for air pollution problems. Similarly, considerable water and toxic pollution is created during pulping, especially with bleached pulp. A typical pulp and integrated mill uses between 4,000-12,000 gallons of water to produce one ton of pulp, and bleached kraft pulping mills were identified in the 1980s as a source of dioxin, a highly toxic pollutant.

Oil refineries use numerous process heaters to heat process streams or to generate steam (boilers) for heating or steam stripping. Incomplete combustion or heaters fired with refinery fuel pitch or residuals are a significant source of air pollution, including carbon monoxide (CO), SO_2, NOX, and $PM_{2.5}$. Of the many production techniques employed at oil refineries catalytic cracking is one of the most significant sources of air pollutants – producing heater flue gas emissions, fugitive emissions, and emissions generated during regeneration of the catalyst. Water pollution concerns are mainly with wastewaters which consist of cooling water, process water, sanitary sewage water, and storm water run-off. Many refineries have had issues with unintentional releases of liquid hydrocarbons to ground water and surface waters. The actual volume of hydrocarbons released are relatively small, however there is the potential to contaminate large volumes of ground water and surface water possibly posing a substantial risk to human health and the environment.

The main processes for steel production use either traditional blast furnaces (integrated mills) or the newer, cleaner electric arc furnaces. The use of blast furnaces is necessarily preceded by two additional production stages: coke-making (coke is produced from coal) and iron-making (molten iron is produced from iron ore and coke). The coke-making process is one of the steel industry's areas of greatest environmental concerns producing both air and water emissions. Air emissions include both fine particles of coke and various sulfur compounds. Water is used to reduce or cool the gases to temperatures at which they can be effectively treated by the gas abatement equipment (roughly 1,000 gallons of water per ton of steel are used for a wet scrubber). On the other hand, the primary raw material for electric arc furnace mills is scrap metal. Since scrap metal is used instead of molten iron, there are no coke-making or iron-making operations associated with steel production, which makes it a much cleaner process than that of blast furnaces. However this process does still produce fine particles and gaseous byproducts which need to be abated.

3. Determinants of Environmental and Economic Performance

We measure the environmental performance of our plants by their emissions of fine particulate matter, sulfur dioxide, toxic releases, biological oxygen demand, and total suspended solids measured per unit of output. Our measure of economic performance is labor productivity (LP). We expect our different measures of plant performance – both economic and environmental – to be systematically related. There are competing explanations for the likely correlations across these different outcome measures. For example, a plant that does especially well on air pollution abatement might also do well on water pollution abatement, if the key unobserved factor is the ability of the plant manager to deal with environmental issues. Alternatively, there could be a negative correlation between performance on air and toxic emissions if the process of filtering particles from air emissions generates toxic sludge that requires disposal.

The relationship between pollution emissions and economic outcomes is similarly ambiguous. Plants with better managers might achieve both higher economic productivity and lower emissions. On the other hand, there might be a negative correlation between economic and environmental performance if managers have to choose between investing in pollution abatement or in productive capital.

We estimate a multi-dimensional model of plant performance for plants in our three industries:

$$Z_{pkt} = f_k(ENFORCE_{pkt}, X_{pt}, X_{ft}, YEAR_t, Z_{pjt}, u_{pkt}) \qquad (1)$$

Here Z_{pkt} measures the performance of plant p at time t along dimension k, including both environmental and economic dimensions: air and water pollution, toxic releases, and labor productivity. ENFORCE is a measure of enforcement activity faced by the plant, expected to raise environmental performance (perhaps at the expense of economic performance). The model includes characteristics of the plant (X_p) and firm (X_f), year dummies ($YEAR_t$) to allow for changes in performance or its definition over time, and other unmeasured factors (u_{pkt}).

Plant characteristics such as age, size, and production technology have been shown in previous studies to be related to both emissions and compliance rates. For example, Shadbegian and Gray (2003) find that in the paper industry pulp mills emit more air pollution per unit of output than non-pulping mills. Furthermore, Gray and Shadbegian (2005) find that older and larger paper plants are less likely to be in compliance with air regulations.

We include several firm characteristics including firm employment as a measure of size and profitability in the model as well to test for possible scale economies in the assistance provided by central headquarters staff to the individual plants. In previous studies firm characteristics such as size and profitability have been related to compliance rates. For example, Helland (1988) finds some evidence that more profitable firms have plants with fewer water pollution violations. Finally, in the labor productivity model we include a measure of the plant’s capital stock as well as other plant characteristics including production technology, age, and pollution abatement spending.

In our final approach to examining the determinants of plant performance we examine the interactions of a plant’s performance across the different dimensions using an SUR model. Estimating a multi-dimensional model of plant performance in different industries allows us to examine the interactions between environmental and economic performance and to examine the robustness of our results across the three industries. We estimate three separate SUR models — one for air emissions, water emissions, and toxic releases. In all three models, we include an equation for labor productivity to go with the emissions equations for that pollution medium, allowing us to test for correlations between the unobserved components of environmental and production performance.

4. Data Description

Research for this study was done at the Census Bureau's Boston Research Data Center, using confidential Census databases developed by the Census's Center for Economic Studies. The principal Census data source is the Longitudinal Research Database (LRD), which contains information on individual manufacturing establishments from the Census of Manufactures and Annual Survey of Manufacturers linked together over time (for a more details concerning LRD data, see McGuckin and Pascoe (1988)). From the LRD we selected 327 pulp and paper mills (mainly SIC 2611 and 2621), 121 oil refineries (SIC 2911), and 83 steel mills (SIC 3312). We gathered the data for 1990-2000; most plants are present in the Census of Manufacturers data for 1992 and/or 1997, while fewer plants are available in non-Census years.

We use labor productivity, LPROD, as our measure of a plant's efficiency, due to limited information on a plant’s capital stock. The sparse nature of our Census data makes it difficult to construct a real capital stock for the plant using a perpetual inventory method. LPROD is calculated as the real value of shipments divided by the number of production hours, and is the dependent variable in our economic performance models. When we want to include a plant's productive efficiency in our models of emissions performance, we use ALPROD, LPROD averaged over all available observations for the period 1990-2000, to reduce the likelihood of 'building in' a negative correlation with our emissions variables, which are measured relative to the plant's capacity. We use both these measures in log form in the regressions.

We capture differences in technology across plants (high-polluting and low-polluting) with a technology dummy variable, DIRTY TECH, indicating that the plant incorporates the higher-polluting production process.[2] Therefore DIRTY TECH=1 for paper mills incorporating a pulping process, for oil refineries using catalytic cracking, and for integrated steel mills.[3] Our control for plant age, OLD, is a dummy variable, indicating whether the plant was in operation before 1972.[4] We control for plant size with the log of plant employment (production workers), PLANTEMP. We include a dummy variable MULTIUNIT indicating if a plant is part of a firm that owns more than one manufacturing plant. Finally, when we model the determinants of labor productivity we include CAPITAL, the real gross book value of a plant's capital stock per production worker hour, to control for differences in capital intensity.

To our LRD data we add data from Census Bureau's annual Pollution Abatement Costs and Expenditures (PACE) survey. The PACE survey provides annual plant-level pollution abatement operating cost data for air and water pollution. We divide pollution abatement

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[2] We could further differentiate our pulp mills by their pulping process (kraft, mechanical etc), however Census Bureau disclosure rules preclude this, since our sample contains too few plants to release coefficients for specific pulping types.

[3] DIRTY TECH for oil refineries is mostly connected to air pollution, but for consistency we include it in the water pollution models as well.

[4] We would like to thank John Haltiwanger for providing the plant age information. In our analysis we used a single dummy to measure plant age (OLD = open before 1972) for two reasons: our sample includes some very old plants, likely to heavily influence any linear (or non-linear) age specification, and concern with environmental issues was not prominent before the 1970s.

operating costs for air and water by a measure of the plant's capacity (where plant capacity is the average of the plant's peak two years of real shipments in $1000s [5]) to get a measure of the pollution abatement expenditure intensity at the plant, APAOC and WPAOC respectively.[6]

To our Census data we merge firm-level information from the Compustat database. The ownership linkage between firms and plants was based on industry directories capturing changes in plant ownership over time. From the industry directories we calculated FIRMPLANTS, the log of the number of other plants owned by the firm in that particular industry. From Compustat data we calculate the log of firm employment, FIRMEMP, and FIRMPROF, the firm's profit rate (net income divided by capital stock). We also include a dummy variable, FIRMSIC, indicating that the firm's primary activity, as identified by Compustat, was the same as the plant's primary activity.[7]

Our environmental performance measures come from several EPA databases: National Emissions Inventory (NEI), Permit Compliance System (PSC), Toxic Release Inventory (TRI), and Compliance Data System (CDS). Our air emissions data come from the NEI database. The emissions data is provided separately for the major criteria air pollutants. In our analysis we focus on fine particulate matter[8] ($PM_{2.5}$) and sulfur dioxide (SO_2), since they are common across all three industries and were the major focus of air pollution regulation for these industries during in the 1990's.[9] We measure the emissions of each pollutant, $PM_{2.5}$ and SO_2 , in log intensity form (the log of emissions in tons per year relative to plant capacity).

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[5] All variables below that are measured relative to plant capacity are measured in this way.
[6] For the TRI analysis we use total pollution abatement operating costs relative to plant size (PAOC).
[7] Regressions include a dummy variable for missing Compustat data, MISSFIRM, which cannot be reported due to Census Bureau disclosure rules.
[8] Particles of 2.5 micrometers or less in diameter.
[9] Relatively few of our emissions reports are based on actual monitored emissions; the majority of emission reports are based on calculated emissions or engineering estimates, based on the capacity of the production process and the design efficiency of the installed pollution abatement equipment.

Our measures of water pollution come from EPA's PCS data set. We use two very common measures of water pollution, biological oxygen demand (BOD) and total suspended solids (TSS). As with our air emissions we measure the emissions of each pollutant, BOD and TSS, in log intensity form (the log of emissions in tons per year, relative to capacity). Our final measure of emissions comes from EPA's TRI data set. The TRI provides detailed information on the disposal of toxic waste from manufacturing plants. We calculate the total TRI discharge intensity for each plant, TOXIC, as the log of annual pounds of toxic environmental releases relative to capacity.[10]

The CDS and PCS also provide annual measures of air and water pollution enforcement activity, respectively, directed towards each plant. To measure air/water pollution enforcement, we use two variables XACT and XINSP (where X = AIR and WATER). XACT is the log of the total number of actions (e.g. notices of violation, penalties, phone calls) directed towards the plant during the year. XINSP is the log of the total number of 'inspection-type' actions (e.g. inspections, emissions monitoring, stack tests). These two different measures of enforcement activity may have different impacts on emissions and may have different degrees of endogeneity with emissions.[11]

Other regulatory pressures expected to influence the level of environmental performance at a plant are NONATTAIN and GREEN VOTE. NONATTAIN, a measure of local regulatory stringency specific to air pollution, is a dummy variable indicating whether the plant is located in a county that failed to attain the ambient air quality standards for PM or SO_2. The attainment

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[10] TRI chemicals are limited to those included in the 'core chemical' list for the 1988 TRI (found at http://www.epa.gov/triexplorer/list-chemical-core-88.htm).
[11] Gray and Shadbegian (2005) found some evidence that compliance with air pollution regulations by plants which are owned by larger firms is less sensitive to inspections and more sensitive to enforcement actions than those owned by smaller firms.

status of each county is published each year in the Federal Register.[12] Plants located in non-attainment areas face stricter regulations than similar plants in attainment areas. For the plants in our sample, non-attainment status is almost always due to excessive fine particulates; sulfur dioxide non-attainment is much less common. Therefore, we consider a plant to be in a non-attainment area if the area is violation of either the ambient air quality standard for PM or SO_2.

We proxy for the state-level regulatory climate with GREEN VOTE, a measure of support for environmental legislation by that state's Congressional delegation. We calculate GREEN VOTE from the League of Conservation Voters scorecard on environmental issues which they produce each year for each member of Congress. We use the average score for the state's House of Representative members in our analysis.

5. Econometric Issues

Several econometric issues arise when we proceed to the estimation of equation (1). First, our data is far from a balanced panel: the air emissions data is from 1990, 1996, and 1999, while the water emissions data is for 1994-2000 and the toxic release data is for 1990-2000, though not all plants are present in all years. Most plants have productivity data for only the two Economic Census years (1992 and 1997), while other plants who happen to be included in the Annual Survey of Manufactures have data from the years between Censuses. The sparse data would complicate the estimation process for multi-equation models: sample sizes diminish rapidly when we require the plant to have simultaneous data for multiple emissions measures and productivity. Rather than estimating a multi-equation model directly, we concentrate on single-equation models. Even when we use an SUR model to allow for correlations in the residuals

[12] We would like to thank Randy Becker, who created this dataset and graciously made it available to us for this project. The data is described in more detail in Becker (2001).

across equations, we only examine one pollution medium at a time: estimating two water pollutants and productivity, two air pollutants and productivity, and toxic releases and productivity, rather than requiring water, air, and toxic data together. We then calculate pairwise correlations in residuals across all of the equations to see whether the unexplained portions of the different pollutants are related to each other, without trying to calculate an SUR model across all pollutants at once.

The sparseness of the data also influences the variable construction. We rely heavily on ‘average’ or ’most recent’ values, rather than insisting on simultaneous data. For example, the pollution abatement cost data ends in 1994, while the water pollution data does not start until 1995 for many plants; we lag the most recent abatement cost values for PAOC in the models, while we use average labor productivity to measure the plant’s production performance.

Finally, any study of enforcement and environmental performance must face the issue of the endogeneity of enforcement. Harrington (1988) suggests a sophisticated explanation of regulator behavior. Harrington develops a model in which an optimal regulatory strategy may well involve focusing on long-run enforcement activity on the few non-compliant plants to punish them for not complying with environmental regulation. Whatever the reason, previous research has had little difficulty identifying an inverse relationship between regulatory activity and compliance behavior: non-complying plants get more enforcement.

We use an instrumental variable (IV) estimator to overcome the potential endogeneity of enforcement activity. In the first stage we use a relatively simple model to predict enforcement activity, focusing on variables that are clearly exogenous with respect to the plant's environmental performance: year dummies, state dummies, DIRTY TECH, OLD, NONATTAIN, and GREEN VOTE. Year dummies allow for changes in enforcement activity over time, while state dummies allow for cross-state differences in enforcement activity (or for differences in reporting of enforcement activity in the CDS and PCS). NONATTAIN controls for different regulatory stringency in different areas, while DIRTY TECH and OLD provide plant characteristics. GREEN VOTE controls for changes over time in the political support for environmental regulation within the state. The lagged predicted values from these first-stage models are then used in the second-stage environmental performance models. One potential problem with any IV method is a weak performance by the first stage models: here we have first-stage R-squares of about 0.05 for water pollution activity and about 0.25 for air pollution activity.

6. Results

Table 1 lists the definitions of the variables used in the analysis, along with their means and standard deviations. We also present the fraction of the variation in each variable that is cross-sectional (CS) and time-series (TS), to get a better understanding of our ability to control for plant-specific and time-specific variation. As often happens with plant-level data, much of the variation in our key variables is cross-sectional, and several variables of interest are fixed over time (making it impossible to estimate their coefficients through a fixed-effect model).

As noted earlier, the pollution variables are measured relative to plant capacity. Most of these measures are relatively high for paper mills, which has the highest values for all the pollutants except BOD. Steel mills have twice as many employees as oil and paper, while oil refineries have especially high values of output, due to the high cost of the crude oil used in production. About three-quarters of all plants were in operation before 1972 and nearly all are owned by multi-unit firms, with the average plant having 4 other plants in the industry owned by the same company.

Tables 2-4 present the basic regression model of the determinants of five pollutant emissions and labor productivity for the three industries: Table 2 shows water pollution, Table 3 shows air pollution, and Table 4 shows toxic releases and labor productivity. Given the large number of regressions involved, we concentrate on identifying the general tendencies across equations, rather than a detailed discussion of each coefficient. The regressions tend to explain one-fifth to one-third of the variation in pollution emissions across plants.

Our focus here is on the connection between performance on production activities and on pollution emissions. We have included both the average labor productivity for the plant (ALPROD) and its interaction with dirty plant technology (DIRTY TECH*ALPROD) to test this relationship. The coefficient on labor productivity is generally negative and often significant. For some of the exceptions (such as oil-air) the interactive term is negative, and large enough to offset the direct positive effect. Only the paper-tri effect shows a net positive effect of productivity on emissions (and that quite small). The interaction term shows that in oil and steel higher productivity matters more for plants with the dirtier production process, though this effect is only occasionally significant.

Not surprisingly, plants which incorporate the dirtier production process (DIRTY TECH) tend to have more emissions. It is more surprising that we see little evidence that older plants are dirtier than younger ones. In fact, 10 of 15 coefficients on OLD are negative (though only 4 are significant). We also see some evidence of diseconomies of scale in pollution control, as plants with greater employment (PLANTEMP) tend to have greater emissions.

We include several firm characteristics in the model, to test for scale economies in the support provided by central headquarters staff to the individual plants. Most of these are connected with the firm size: being multi-unit, having a large number of plants in the industry, or large firm employment. The surprise is that the coefficients are positive as often as negative, providing little evidence that bigger firms help individual plants to reduce emissions. The other firm characteristics – having its primary SIC in this industry (FIRMSIC) and return on assets (FIRMPROF) do not show much of a pattern of results.

Our models also included several variables connected with regulatory activity. The main variables are for the number of enforcement actions (WATERACT and AIRACT) and inspections (WATERINSP and AIRINSP) faced by the plant. As noted earlier, we use predicted values of these variables in order to avoid concerns with endogeneity of enforcement. We find reasonably consistent results across different pollutants, with less pollution where enforcement actions are common and more pollution where inspections are common (but do not have a clear explanation for the differing signs of the effects). The PAOC variables generally enter positively, appearing to indicate that plants which spend more for pollution abatement have greater emissions, or (more likely) that plants with greater emissions problems need to spend more on pollution abatement. This result, though apparently surprising, is similar to that found in Shadbegian and Gray (2003). Finally, the VOTE variable (reflecting political support for environmental regulation) enters negatively for water and toxic releases, but positively for air emissions. This may be driven by VOTE reflecting more of a state or local pressure on firms to abate pollution, which may be stronger for emissions that have most of their potential negative health effects nearby, such as water and toxic pollution.

The labor productivity models in Table 4 show higher output per worker hour when a plant is using the dirtier technology, when the plant has a high capital-labor ratio, and when the plant is relatively new (post-1972). In previous work Gray and Shadbegian (2002, 2003a) found that plants spending more on PAOC had lower total factor productivity. In this case we find PAOC is associated with significantly lower labor productivity only for steel mills.

We explore an alternative measure of the connection between the different performance measures in Tables 5-7. These tables present the SUR models, which allow for correlations in the residuals across equations. As noted earlier, we run the regressions for each medium separately, first water, then air, then toxic emissions. In all three cases, we include an equation for productivity to go with the emissions equations for that pollution medium, allowing us to test for correlations between the unobserved components of emissions and production performance. In order to maximize the amount of information available to test for the emissions-production relationship, we omit the ALPROD and DIRTY TECH*ALPROD variables from the emissions models. As shown by the Breusch-Pagan tests, we find a significant correlation among the set of residuals for each of the models.

We get a sense of the magnitude of these effects in Table 8, which shows the pairwise correlations between emissions and productivity for each industry. For all industries and all media, there are significant positive relationships between the pairs of pollutants within each medium (BOD and TSS, or SO_2 and $PM_{2.5}$). More often than not (14 of 24 cases), we also find positive relationships between emissions of pollutants in different media, though exceptions are common (i.e. negative correlations for the paper SO_2 – water, for the oil industry air-water, and for the steel industry SO_2 – BOD, toxic-air and toxic-TSS, and. Finally, there tend to be negative correlations between the productivity residuals and each of the emissions residuals (36 of 45 cases). Although these are not always significant, they provide some confirmation for the earlier result that plants with higher productivity have lower emissions.

7. Concluding Remarks

This paper uses a broad range of data, covering 3 industries and 5 pollutants, to see how a plant's performance on production efficiency is related to its performance on emissions reductions. One (negative) conclusion from the research is that we do not find perfectly consistent patterns in coefficients across all the different industries and pollutants. This is not surprising – there are different production processes in each industry, and different factors influencing each pollutant – but makes it more difficult to generalize (if we had only considered one industry and one or two pollutants, a consistent set of coefficients would have been more likely). Different observations are missing different combinations of performance measures, making it difficult to estimate simultaneous-equation models without large reductions in sample size.

Despite these difficulties, we see some patterns. In most cases, plants with higher labor productivity also have lower emissions. This also holds in the SUR analyses, where plants doing surprisingly well on emissions tend to do surprisingly well on productivity. One possible explanation is the role of managerial quality in driving both emissions reductions and productivity increases. We find little evidence for economies of scale in pollution control, either at the plant or firm level, while older plants do no worse (or even a bit better). Regulatory variables give mixed results, with enforcement actions (but not inspections) associated with lower emissions. The stronger negative impacts for GREEN VOTE on water and toxic pollution may be due to those being more local pollutants than air, and hence more likely to be the subject of local political pressure.

Our future research in this area is likely to follow a more narrowly defined set of analyses (perhaps one industry, or one pollution medium), given the complications we found here in establishing patterns in coefficients across 18 equations. We will try to test additional measures of firm strategy, including compliance behavior at other plants, as well as differences across states in the impact of regulatory activity on emissions and productivity. We will also examine patterns of spatial correlation in environmental and productivity performance, extending work we've done with air pollution emissions and compliance in Gray and Shadbegian (2003b).

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Table 1 – Summary Statistics

VARIABLE	PAPER MEAN	SD	%CS	%TS	OIL MEAN	SD	%CS	%TS	STEEL MEAN	SD	%CS	%TS
BOD	7.66	52.36	0.17	0.00	22.70	438.42	0.16	0.01	0.12	0.38	0.54	0.01
Log(BOD)	1.48	0.92	0.83	0.01	0.11	0.50	0.22	0.02	0.09	0.21	0.70	0.01
TSS	11.16	28.43	0.60	0.01	0.49	5.31	0.15	0.01	1.35	4.17	0.47	0.02
Log(TSS)	1.78	1.08	0.89	0.01	0.15	0.35	0.49	0.01	0.48	0.67	0.86	0.00
SO_2	7.80	17.03	0.95	0.00	3.56	6.08	0.57	0.02	1.50	4.09	0.64	0.02
Log(SO_2)	1.47	1.13	0.81	0.00	1.09	0.85	0.79	0.01	0.50	0.74	0.79	0.02
$PM_{2.5}$	0.97	1.67	0.64	0.01	0.20	0.28	0.72	0.01	0.53	0.93	0.75	0.00
Log($PM_{2.5}$)	0.50	0.53	0.79	0.01	0.16	0.18	0.70	0.02	0.33	0.39	0.69	0.01
TOXIC	2.10	4.07	0.75	0.00	0.47	1.24	0.92	0.01	0.65	0.36	0.55	0.00
Log(TOXIC)	0.79	0.76	0.85	0.02	0.28	0.36	0.83	0.02	0.28	0.48	0.58	0.01
LPROD	189.15	107.64	0.74	0.15	1014.94	528.12	0.65	0.14	222.45	114.91	0.74	0.11
Log(LPROD)	5.12	0.50	0.75	0.18	6.79	0.54	0.63	0.12	5.30	0.47	0.75	0.14
AVGPROD	193.20	92.12	1.00	0.00	1210.38	968.10	1.00	0.00	226.54	99.15	1.00	0.00
Log(AVGPROD)	5.17	0.43	1.00	0.00	6.97	0.47	1.00	0.00	5.34	0.41	1.00	0.00
DIRTY TECH	0.65	0.48	1.00	0.00	0.76	0.43	0.89	0.01	0.38	0.49	1.00	0.00
OLD	0.78	0.42	1.00	0.00	0.79	0.41	1.00	0.00	0.68	0.47	1.00	0.00
PLANTEMP	436.61	348.17	0.93	0.00	327.19	283.78	0.97	0.00	1185.65	1471.32	0.97	0.00
Log(PLANTEMP)	5.75	0.86	0.95	0.00	5.40	0.98	0.97	0.01	6.49	1.06	0.96	0.00
CAPITAL	46.06	123.50	0.08	0.55	86.04	180.42	0.06	0.67	33.54	65.83	0.06	0.61
Log(CAPITAL)	1.28	1.98	0.04	0.90	2.40	2.19	0.17	0.67	2.06	1.75	0.09	0.76
MULTIUNIT	0.97	0.16	0.71	0.01	0.99	0.08	0.87	0.01	0.92	0.27	0.96	0.00
FIRMSIC	0.44	0.50	0.74	0.01	0.61	0.49	0.79	0.04	0.69	0.46	0.75	0.02
Log(FIRMEMP)	5.70	5.01	0.67	0.02	6.08	5.01	0.64	0.10	6.30	4.04	0.67	0.05
FIRMPROF	0.89	26.48	0.12	0.01	2.22	3.57	0.39	0.08	-0.05	5.79	0.29	0.15
FIRMPLANTS	12.27	11.44	0.86	0.00	5.99	4.49	0.86	0.00	5.36	4.28	0.95	0.00
Log(WATERACT)	2.36	2.65	0.72	0.26	4.97	3.00	0.81	0.18	2.91	2.61	0.73	0.26
Log(WATERINSP)	0.79	1.88	0.66	0.31	1.94	1.87	0.69	0.28	1.13	2.36	0.79	0.21
Log(AIRACT)	4.56	3.17	0.82	0.21	6.37	3.52	0.87	0.16	4.85	3.88	0.88	0.10
Log(AIRINSP)	1.62	0.67	0.89	0.06	2.08	0.99	0.95	0.03	2.02	1.07	0.95	0.01
WPAOC	0.02	0.27	0.14	0.00	0.00	0.02	0.23	0.00	0.00	0.01	0.89	0.00
APAOC	0.00	0.02	0.21	0.00	0.00	0.01	0.37	0.01	0.01	0.01	0.84	0.00
PAOC	0.03	0.40	0.19	0.00	0.13	3.96	0.10	0.01	0.01	0.01	0.85	0.00
GREEN VOTE	48.90	18.96	0.79	0.08	38.47	16.71	0.73	0.11	46.01	16.46	0.76	0.11
NONATTAIN	0.22	0.41	0.74	0.00	0.34	0.47	0.81	0.00	0.65	0.48	0.74	0.00

Variable Definitions

BOD	=	Biological oxygen demand i at time t (in tons/capacity)
TSS	=	Total suspended solids i at time t (in tons/capacity)
SO_2	=	Sulfur dioxide emissions i at time t (in tons/capacity)
$PM_{2.5}$	=	Particulate matter of 2.5 millimeters or less in diameter at plant i at time t (in tons/capacity)
TOXIC	=	TRI chemical releases at plant i at time t (in tons/capacity)
LPROD	=	Labor productivity, real shipments per production worker hour, at plant i at time t
ALPROD	=	Average labor productivity over the entire time period at plant i
DIRTY TECH	=	A dummy variable = 1 for paper mills with pulping facilities, oil refineries using catalytic cracking and for blast furnace steel mills
OLD	=	A dummy variable = 1 if a plant was open prior to 1972
PLANTEMP	=	Number of production workers at the plant at plant i at time t
CAPITAL	=	Real gross book value of capital per production worker hour at the plant at plant i at time t
MULTIUNIT	=	A dummy variable = 1 if the plant is part of a multi-plant firm
FIRMSIC	=	A dummy variable = 1 if the firm's primary activity is the same as the plant's
FIRMEMP	=	Employment the firm that owns plant i at time t
FIRMPROF	=	Firm profit rate (net earnings/capital stock) at plant i at time t
FIRMPLANTS	=	Number of plants the firm owns in the same industry at plant i at time t
WATERACT	=	The predicted number of water actions at plant i at time t-2
WATERINSP	=	The predicted number of water inspections at plant i at time t-2
AIRACT	=	The predicted number of air actions at plant i at time t-2
AIRINSP	=	The predicted number of air inspections at plant i at time t
WPAOC	=	Water pollution abatement operating costs/plant capacity at plant i at time t-2
APAOC	=	Air pollution abatement operating costs/plant capacity at plant i at time t-2
PAOC	=	Total pollution abatement operating costs/plant capacity at plant i at time t-2
GREEN VOTE	=	A state's pro-environmental Congressional voting score (League of Conservation Voters)
NONATTAIN	=	A dummy variable for plant i at time t = 1 if plant i is located in an area that is not in compliance with National Air Quality Standards for both sulfur dioxide and fine particulates at time t

Table 2
Water Pollution Discharges
(OLS; |t-statistics| in parentheses)

	PAPER		OIL		STEEL	
	(1)	(2)	(3)	(4)	(5)	(6)
	BOD	**TSS**	**BOD**	**TSS**	**BOD**	**TSS**
CONSTANT	5.3438	4.1396	-0.0169	-0.2602	1.3749	3.5606
	(6.16)	(4.27)	(0.02)	(0.45)	(4.52)	(3.98)
ALPROD	-0.5040	-0.2217	0.0265	0.0485	-0.0686	-0.6812
	(3.21)	(1.26)	(0.22)	(0.59)	(1.65)	(5.55)
ALPROD*	0.4999	0.1911	-0.2611	-0.1340	-0.1793	-0.9585
DIRTY TECH	(2.86)	(0.98)	(1.78)	(1.34)	(2.73)	(4.95)
DIRTY TECH	-2.0458	-0.1072	1.9298	1.0060	1.0579	5.4284
	(2.29)	(0.11)	(1.87)	(1.44)	(3.03)	(5.29)
OLD	-0.1783	-0.1616	-0.0250	-0.0912	0.0422	-0.0172
	(3.10)	(2.51)	(0.32)	(1.71)	(1.28)	(0.18)
PLANTEMP	0.0136	0.0610	-0.0502	-0.0239	-0.0962	0.1644
	(0.39)	(1.55)	(1.27)	(0.89)	(5.00)	(2.90)
MULTIUNIT	+	+			--	--
FIRMSIC	-0.1842	-0.0725	0.0557	0.0922	-0.2341	-0.2973
	(2.71)	(0.96)	(0.56)	(1.37)	(3.76)	(1.62)
FIRMEMP	-0.1562	-0.2256	0.0003	-0.0005	0.0090	0.0693
	(4.01)	(5.18)	(0.01)	(0.02)	(0.55)	(1.44)
FIRMPROF	-0.0042	-0.0039	-0.0019	-0.0017	-0.0002	0.0075
	(0.96)	(0.80)	(0.18)	(0.24)	(0.09)	(1.04)
FIRMPLANTS	0.0247	0.0275	0.0013	0.0020	0.0103	0.0799
	(8.05)	(8.04)	(0.17)	(0.39)	(2.42)	(6.40)
WPAOC	18.2521	18.7926	12.9246	41.2522	12.2522	-46.0034
	(6.52)	(6.00)	(1.03)	(4.86)	(2.95)	(3.76)
WATERACT	0.0174	-0.0000	-0.0021	-0.0053	-0.0408	-0.0105
	(1.41)	(0.00)	(0.19)	(0.68)	(4.61)	(0.40)
WATERINSP	-0.0027	-0.0369	0.0097	0.0100	0.0372	0.0351
	(0.15)	(1.87)	(0.53)	(0.82)	(4.55)	(1.46)
GREEN VOTE	-0.0103	-0.0143	0.0005	0.0005	-0.0012	-0.0020
	(7.08)	(8.76)	(0.31)	(0.47)	(1.38)	(0.76)
R2	0.29	0.35	0.07	0.14	0.40	0.48

Table 3
Air Pollution Emissions
(OLS; |t-statistics| in parentheses)

	PAPER		OIL		STEEL	
	(1)	(2)	(3)	(4)	(5)	(6)
	SO2	**PM2.5**	**SO2**	**PM2.5**	**SO2**	**PM2.5**
CONSTANT	3.8838	0.9259	0.1967	-0.0115	-1.6043	1.0256
	(3.07)	(1.71)	(0.12)	(0.03)	(1.46)	(1.55)
ALPROD	-0.7837	-0.1589	0.2036	0.0370	-0.0226	-0.1367
	(3.86)	(1.83)	(1.05)	(0.87)	(0.12)	(1.24)
ALPROD*	0.3172	0.2147	-0.6269	-0.0757	-0.5077	0.0387
DIRTY TECH	(1.13)	(1.78)	(2.54)	(1.40)	(1.69)	(0.22)
DIRTY TECH	-1.3638	-0.7651	5.0905	0.6456	3.0052	-0.0645
	(0.94)	(1.23)	(2.92)	(1.69)	(1.86)	(0.07)
OLD	-0.0591	-0.0722	0.0226	0.0647	0.1095	-0.0174
	(0.46)	(1.30)	(0.16)	(2.06)	(0.68)	(0.18)
PLANTEMP	0.1141	0.0174	-0.1517	-0.0330	0.1679	0.0028
	(1.54)	(0.55)	(2.18)	(2.15)	(2.59)	(0.07)
MULTIUNIT	0.0527	0.0429	+	-	+	-
	(0.19)	(0.35)				
FIRMSIC	0.2906	-0.0313	-0.1188	-0.0421	0.1718	0.0648
	(1.91)	(0.48)	(0.58)	(0.94)	(0.87)	(0.55)
FIRMEMP	-0.0202	0.0459	-0.0580	0.0001	0.0348	-0.0260
	(0.26)	(1.40)	(0.83)	(0.01)	(0.60)	(0.74)
FIRMPROF	0.0175	-0.0013	0.0026	-0.0038	0.0109	0.0096
	(1.76)	(0.31)	(0.10)	(0.70)	(0.97)	(1.42)
FIRMPLANTS	-0.0021	0.0002	-0.0010	-0.0018	0.0340	0.0205
	(0.36)	(0.07)	(0.06)	(0.51)	(2.17)	(2.18)
WPAOC	11.5418	9.8438	12.0494	3.1529	22.9737	6.1017
	(1.50)	(2.99)	(1.11)	(1.32)	(2.55)	(1.13)
AIRACT	-0.0201	-0.0276	-0.0098	-0.0181	-0.0335	-0.0134
	(0.75)	(2.41)	(0.34)	(2.84)	(1.41)	(0.94)
AIRINSP	0.4439	0.1087	0.1812	0.0535	0.0689	0.1066
	(4.21)	(2.41)	(2.07)	(2.78)	(0.94)	(2.43)
GREEN VOTE	0.0014	-0.0076	-0.0023	0.0006	0.0000	0.0010
	(0.40)	(5.33)	(0.68)	(0.84)	(0.01)	(0.54)
NONATTAIN	-0.2978	-0.0390	-0.0818	-0.1003	0.0384	-0.0161
	(2.42)	(0.74)	(0.65)	(3.64)	(0.30)	(0.21)
R2	0.16	0.29	0.22	0.16	0.39	0.21
OBSERVATIONS	459	459	246	246	164	164

Table 4
Toxic Releases; Labor Productivity
(OLS; |t-statistics| in parentheses)

	PAPER		OIL		STEEL	
	(1)	(2)	(3)	(4)	(5)	(6)
	TOXIC	**LPROD**	**TOXIC**	**LPROD**	**TOXIC**	**LPROD**
CONSTANT	0.5976	3.9550	0.3950	5.9433	1.3538	4.5427
	(1.67)	(28.62)	(1.44)	(22.93)	(3.57)	(29.42)
ALPROD	-0.1480		-0.0858		-0.3669	
	(2.54)		(2.67)		(6.20)	
ALPROD * DIRTY TECH	0.3261		-0.4050		0.3277	
	(4.57)		(8.73)		(3.26)	
DIRTY TECH	-1.0318	0.2016	2.9081	0.1613	-1.8446	0.0733
	(2.84)	(12.65)	(8.91)	(4.44)	(3.44)	(2.36)
OLD	-0.0063	-0.2580	-0.0170	-0.0846	0.0000	-0.2729
	(0.20)	(14.46)	(0.61)	(2.25)	(0.00)	(9.00)
PLANTEMP	0.1126		0.0189		0.1006	
	(6.31)		(1.37)		(4.81)	
MULTIUNIT	-0.0019	-0.0002	+	+	++	--
	0.02)	(0.00)				
FIRMSIC	-0.0942	0.0107	0.0340	0.2988	0.0226	0.0186
	(2.59)	(0.50)	(0.90)	(5.80)	(0.30)	(0.36)
FIRMEMP	0.0395	0.0913	0.0214	0.0056	0.0022	0.0802
	(2.11)	(8.40)	(1.52)	(0.29)	(0.10)	(5.74)
FIRMPROF	-0.0003	-0.0004	-0.0063	0.0034	0.0058	0.0106
	(0.76)	(1.56)	(1.78)	(0.65)	(1.72)	(4.56)
FIRMPLANTS	0.0039	-0.0028	0.000	-0.0049	-0.0000	0.0189
	(2.91)	(3.44)	(0.26)	(1.08)	(0.00)	(5.13)
PAOC	0.0181	0.0056	0.0010	0.0014	1.1920	-12.6587
	(0.48)	(0.30)	(0.43)	(0.37)	(0.74)	(12.49)
GREEN VOTE	-0.0089		-0.0038		-0.0001	
	(12.14)		(5.71)		(0.11)	
CAPITAL		0.0839		0.0834		0.1249
		(6.81)		(6.90)		(8.69)
R2	0.37	0.32	0.29	0.25	0.15	0.49
Observations	2435	3115	876	1058	690	823

Table 5
Water Pollution Discharges; Labor Productivity
(SUR; |t-statistics| in parentheses)

		OIL			**PAPER**			**STEEL**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	BOD	**TSS**	**LPROD**	**BOD**	**TSS**	**LPROD**	**BOD**	**TSS**	**LPROD**
CONSTANT	3.0413	3.1019	4.5693	0.0000	0.0000	0.0000	0.9961	-0.1280	5.2822
	(6.52)	(5.97)	(20.25)	(.)	(.)	(.)	(5.18)	(0.20)	(19.27)
DIRTY TECH	0.4712	0.8472	0.2698	0.0969	0.0655	0.0392	0.1233	0.4680	-0.0582
	(7.38)	(11.92)	(10.09)	(1.37)	(1.37)	(0.68)	(4.24)	(4.82)	(1.17)
OLD	-0.1577	-0.1485	-0.2198	-0.0219	-0.0899	-0.0836	0.0414	0.0093	-0.1347
	(2.85)	(2.41)	(9.02)	(0.29)	(1.74)	(1.27)	(1.29)	(0.09)	(2.53)
PLANTEMP	0.0161	0.0651		-0.0395	-0.0167		-0.0892	0.2042	
	(0.47)	(1.71)		(1.06)	(0.66)		(4.82)	(3.50)	
MULTIUNIT	+	+	-	+	+	++	--	--	--
FIRMSIC	-0.2036	-0.0798	-0.0178	0.0379	0.0876	0.2060	-0.2261	-0.1881	-0.3009
	(3.03)	(1.07)	(0.58)	(0.39)	(1.35)	(2.46)	(3.76)	(0.95)	(3.16)
FIRMEMP	-0.1839	-0.2386	0.0606	-0.0033	-0.0019	0.0038	-0.0070	-0.0486	0.0923
	(4.89)	(5.69)	(3.52)	(0.09)	(0.08)	(0.13)	(0.46)	(0.96)	(3.81)
FIRMPROF	-0.0056	-0.0045	0.0015	-0.0023	-0.0017	0.0063	-0.0022	-0.0085	0.0156
	(1.29)	(0.93)	(0.77)	(0.22)	(0.25)	(0.72)	(0.95)	(1.08)	(3.72)
FIRMPLANTS	0.0265	0.0283	-0.0020	0.0020	0.0024	-0.0015	0.0066	0.0479	0.0331
	(8.84)	(8.48)	(1.43)	(0.27)	(0.49)	(0.23)	(1.68)	(3.69)	(5.34)
WPAOC	18.6115	19.2526		22.6790	44.4254		14.2794	-28.1742	
	(7.01)	(6.51)		(2.16)	(6.26)		(3.58)	(2.22)	
WATERACT	0.0201	0.0011		-0.0041	-0.0064		-0.0395	-0.0041	
	(1.64)	(0.08)		(0.37)	(0.86)		(4.61)	(0.15)	
WATERINSP	-0.0060	-0.0376		0.0056	0.0083		0.0330	0.0098	
	(0.35)	(1.94)		(0.32)	(0.71)		(4.20)	(0.40)	
GREEN VOTE	-0.0103	-0.0141		0.0001	0.0004		-0.0006	0.0014	
	(7.25)	(8.96)		(0.07)	(0.37)		(0.72)	(0.55)	
CAPITAL			0.0370			0.0346			0.0717
			(1.78)			(1.65)			(3.08)
PAOC			-2.2772			0.0008			-13.4074
			(5.67)			(0.24)			(5.28)
R2	0.28	0.35	0.28	0.05	0.14	0.29	0.36	0.27	0.53
OBSERVATIONS	1174	1174	1174	377	377	377	255	255	255
Breusch-Pagan		620.93			10.44			84.76	
(p-value)		(0.000)			(0.015)			(0.000)	

Table 6

Air Pollution Emissions; Labor Productivity
(SUR; |t-statistics| in parentheses)

	PAPER			OIL			STEEL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SO2	**PM2.5**	**LPROD**	**SO2**	**PM2.5**	**LPROD**	**SO2**	**PM2.5**	**LPROD**
CONSTANT	0.0000	0.3045	4.4949	0.0000	0.0000	0.0000	-1.7438	0.2365	0.0000
	(.)	(0.78)	(14.89)	(.)	(.)	(.)	(2.85)	(0.65)	(.)
DIRTY TECH	0.1460	0.3301	0.1935	0.6798	0.1129	0.0924	0.2597	0.1395	0.0315
	(0.98)	(5.24)	(4.70)	(4.84)	(3.70)	(1.27)	(1.86)	(1.69)	(0.48)
OLD	-0.0289	-0.0808	-0.1119	0.0842	0.0702	-0.1674	0.0764	0.0387	-0.3859
	(0.23)	(1.50)	(2.46)	(0.61)	(2.36)	(2.14)	(0.55)	(0.47)	(5.60)
PLANTEMP	0.1200	0.0109		-0.1347	-0.0308		0.1841	-0.0053	
	(1.67)	(0.35)		(2.00)	(2.10)		(3.02)	(0.15)	
MULTIUNIT	0.0640	0.0322	0.0265	+	-	+	+	-	-
	(0.23)	(0.27)	(0.26)						
FIRMSIC	0.3641	-0.0199	-0.1134	-0.1673	-0.0452	0.0957	0.1224	0.0660	0.0890
	(2.41)	(0.31)	(2.06)	(0.85)	(1.06)	(0.86)	(0.66)	(0.60)	(0.86)
FIRMEMP	-0.0934	0.0343	0.0862	-0.0570	-0.0003	-0.0118	0.0205	-0.0347	0.1240
	(1.25)	(1.09)	(3.15)	(0.84)	(0.02)	(0.31)	(0.38)	(1.09)	(4.23)
FIRMPROF	0.0129	-0.0025	0.0044	0.0026	-0.0036	0.0268	0.0084	0.0084	0.0124
	(1.31)	(0.59)	(1.22)	(0.11)	(0.69)	(1.95)	(0.80)	(1.33)	(2.14)
FIRMPLANTS	-0.0001	0.0003	-0.0016	0.0009	-0.0017	-0.0006	0.0307	0.0166	0.0165
	(0.02)	(0.12)	(0.74)	(0.06)	(0.52)	(0.07)	(2.12)	(1.94)	(2.14)
WPAOC	12.3841	10.0042		12.1583	3.0810		28.8704	8.4428	
	(1.64)	(3.10)		(1.15)	(1.34)		(3.63)	(1.80)	
WATERACT	-0.0184	-0.0279		-0.0111	-0.0182		-0.0309	-0.0131	
	(0.70)	(2.49)		(0.39)	(2.98)		(1.39)	(1.01)	
WATERINSP	0.4310	0.1087		0.2026	0.0556		0.0858	0.1024	
	(4.17)	(2.46)		(2.39)	(3.02)		(1.27)	(2.60)	
GREEN VOTE	0.0013	-0.0079		-0.0030	0.0006		0.0005	0.0008	
	(0.41)	(5.83)		(0.92)	(0.79)		(0.16)	(0.48)	
NONATTAIN	-0.3058	-0.0545		-0.0370	-0.0954		0.0409	-0.0126	
	(2.57)	(1.07)		(0.31)	(3.63)		(0.34)	(0.18)	
CAPITAL			-0.0641			0.0447			0.1097
			(1.83)			(1.81)			(3.33)
PAOC			-0.0200			-8.3901			-8.1674
			(0.55)			(2.32)			(3.72)
R2	0.12	0.29	0.23	0.19	0.16	0.17	0.37	0.20	0.51
OBSERVATIONS	459	459	459	246	246	246	164	164	164
Breusch-Pagan		68.27			51.04			33.73	
(p-value)		(0.000)			(0.000)			(0.000)	

Table 7
Toxic Releases; Labor Productivity
(SUR; |t-statistics| in parentheses)

	PAPER		OIL		STEEL	
	(1)	(2)	(3)	(4)	(5)	(6)
	TOXIC	**LPROD**	**LTRIC**	**LPROD**	**TOXIC**	**LPROD**
CONSTANT	-0.0787 (0.35)	4.2197 (28.75)	-0.0642 (0.32)	5.8581 (22.41)	-0.4736 (2.06)	4.4023 (25.05)
DIRTY TECH	0.6368 (20.52)	0.1919 (10.77)	0.0697 (2.30)	0.0985 (2.61)	-0.1039 (2.27)	0.0275 (0.82)
OLD	-0.0247 (0.82)	-0.2403 (12.94)	0.0394 (1.30)	-0.1081 (2.81)	0.1071 (2.40)	-0.2350 (7.05)
PLANTEMP	0.1168 (6.60)		0.0257 (1.82)		0.0990 (4.78)	
MULTIUNIT	-0.0173 (0.21)	0.0139 (0.27)	+	++	++	--
FIRMSIC	-0.0967 (2.66)	-0.0098 (0.43)	-0.0460 (1.13)	0.2982 (5.72)	0.0229 (0.30)	0.0439 (0.77)
FIRMEMP	0.0355 (1.93)	0.0756 (6.61)	0.0018 (0.12)	0.0336 (1.71)	-0.0205 (0.93)	0.0880 (5.50)
FIRMPROF	-0.0003 (0.64)	-0.0005 (1.79)	-0.0053 (1.36)	-0.0004 (0.07)	0.0041 (1.22)	0.0123 (4.85)
FIRMPLANTS	0.0042 (3.11)	-0.0028 (3.31)	0.0053 (1.57)	-0.0093 (2.12)	-0.0039 (0.68)	0.0161 (3.93)
WPAOC	0.0151 (0.40)	0.0137 (0.58)	0.0003 (0.11)	0.0013 (0.39)	2.9059 (2.02)	-11.6942 (11.02)
GREEN VOTE	-0.0092 (12.95)		-0.0037 (5.38)		-0.0002 (0.22)	
CAPITAL		0.0580 (4.43)		0.0524 (4.62)		0.1239 (7.85)
R2	0.37	0.33	0.11	0.26	0.10	0.46
OBSERVATIONS	2435	2435	876	876	690	690
Breusch-Pagan (p-value)	6.84 (0.009)		94.79 (0.000)		12.49 (0.000)	

Table 8
SUR Residual Correlations

PAPER

	BOD	TSS	SO2	PM2.5	TOXIC	LPRODW	LPRODA	LPRODT
BOD	1.0000							
TSS	0.7272*	1.0000						
SO2	-0.0907	-0.0735	1.0000					
PM2.5	0.1738*	0.1614*	0.3366*	1.0000				
TOXIC	0.1959*	0.2150*	0.1378*	0.2652*	1.0000			
LPRODW	-0.0114	-0.0026	-0.1155*	-0.0111	0.0262	1.0000		
LPRODA	-0.0108	-0.0045	-0.1969*	-0.0274	0.0591*	0.3764*	1.0000	
LPRODT	-0.0110	-0.0033	-0.1783*	-0.0131	0.0560*	0.4036*	0.8554*	1.0000

OIL

	BOD	TSS	SO2	PM2.5	TOXIC	LPRODW	LPRODA	LPRODT
BOD	1.0000							
TSS	0.1575*	1.0000						
SO2	-0.0498	-0.1539	1.0000					
PM2.5	-0.0850	-0.1015	0.4549*	1.0000				
TOXIC	0.1293*	0.2162*	0.1400*	0.1411*	1.0000			
LPRODW	-0.0585	-0.0279	-0.0166	0.0006	-0.2139*	1.0000		
LPRODA	0.0038	-0.0086	-0.0243	0.0033	-0.0040	0.0017	1.0000	
LPRODT	-0.0575	-0.0235	-0.0170	0.0047	-0.3375*	0.6556*	0.0176	1.0000

STEEL

	BOD	TSS	SO2	PM2.5	TOXIC	LPRODW	LPRODA	LPRODT
BOD	1.0000							
TSS	0.4119*	1.0000						
SO2	-0.0482	0.0995	1.0000					
PM2.5	0.4437*	0.3850*	0.4079*	1.0000				
TOXIC	0.0336	-0.1090*	-0.0626	-0.0226	1.0000			
LPRODW	-0.1621*	-0.4074*	0.0019	-0.1688*	-0.1330*	1.0000		
LPRODA	-0.0212	-0.0563	-0.0136	-0.2115*	-0.0237	0.1057*	1.0000	
LPRODT	-0.1273*	-0.3508*	0.0028	-0.1991*	-0.1398*	0.8684*	0.1522*	1.0000